Artificial Intelligence in Gastrointestinal Endoscopy

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Abstract

Gastrointestinal (GI) complications frequently necessitate intensive care unit (ICU) admission. Additionally, critically ill patients also develop GI complications requiring further diagnostic and therapeutic interventions. However, these patients form a vulnerable group, who are at risk for developing side effects and complications. Every effort must be made to reduce invasiveness and ensure safety of interventions in ICU patients. Artificial intelligence (AI) is a rapidly evolving technology with several potential applications in healthcare settings. ICUs produce a large amount of data, which may be employed for creation of AI algorithms, and provide a lucrative opportunity for application of AI. However, the current role of AI in these patients remains limited due to lack of large-scale trials comparing the efficacy of AI with the accepted standards of care.

Key Words: Artificial intelligence; Critical care; Gastroenterology; Hepatology; Intensive care unit; Machine learning

Core Tip: The scope and applications of artificial intelligence (AI) are rapidly increasing. It is being increasingly applied in various fields, even in healthcare settings. The data generated by critically ill patients admitted in intensive care units (ICUs) is huge, which may be helpful in developing AI algorithms aimed to aid in their management. Patients with primary gastrointestinal diseases may frequently require ICU admission for management of advanced disease or related complications. Use of AI may aid the critical care physicians in managing such patients by helping in early diagnosis, prediction of complications, assessing response to therapy and overall prognostication.

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INTRODUCTION

Artificial intelligence (AI), in simple terms, may be defined as the simulation of human intelligence in machines which are programmed to react like humans, mimicking their actions by means of multi-disciplinary approach[1]. Unlike human mind, which can assimilate only a finite amount of data, machines can accumulate and process unlimited amount of data which can be used in different applications. AI is increasingly influencing every aspect of our life, including healthcare[2].

AI is a complex and rapidly evolving technology. More subsets of AI are being introduced regularly, and each of them have their own unique properties, advantages and limitations. Certain subsets of AI are more commonly employed in healthcare settings than others. The broad subsets of AI include machine learning (ML), deep learning, and cognitive computing. ML involves learning from the prior data to predict the future data. Artificial neural network (ANN) is a subset of ML inspired by the neuronal connections of the human brain. Its further subsets include deep neural network and convolutional neural network (CNN). Other AI algorithms commonly employed in healthcare settings include decision trees, random forest, support vector machines (SVMs), and Naïve Bayes.

Modern intensive care units (ICUs) produce a vast amount of data which is conducive for formation of AI algorithms [2]. A significant proportion of ICU patients are admitted with gastrointestinal (GI) disease or develop GI complications during their ICU course, necessitating further diagnostic and therapeutic interventions. As these patients form a vulnerable group, prone to develop side effects and complications, all measures must be undertaken to reduce invasiveness and ensure safety of ICU procedures. AI can potentially aid the critical care physicians by helping in early diagnosis, predicting complications and response to therapy and providing clinical prognostication in several GI disorders in critically ill patients (Table 1).

PANCREATIC DISORDERS

Almost 25% patients with acute pancreatitis (AP) develop complications or organ failure necessitating ICU admission[3]. Severe acute pancreatitis (SAP) is associated with high morbidity and mortality, requiring intensive monitoring and organ support. Early recognition of risk factors associated with progression to severe disease and development of complications, may help in initiating therapeutic measures and improve outcomes.

Diagnosis

Diagnosis of AP is based on the clinical presentation, laboratory parameters (serum amylase and lipase levels) and imaging (ultrasonography/computed tomography scans). As per the revised Atlanta classification, two out of three diagnostic criteria should be positive to make the diagnosis[4]. However, diagnosis may sometimes be missed due to non-specific clinical presentation, difficulty in imaging and low sensitivity of the revised Atlanta criteria, which may delay the treatment[5].

Integration of AI technology may aid in early diagnosis of acute pancreatitis[6]. ANNs can accurately diagnose AP using clinical and radiological data[7]. In 10%–20% of AP cases, acute necrotizing pancreatitis (ANP) develops, thus further increasing the risk of morbidity and mortality[8,9]. AI based models may also be useful in diagnosing acute necrotizing pancreatitis, which may affect treatment and prognosis[10].

Severity prediction and assessment

Several clinical scores, based on clinical, laboratory, and radiological risk factors, have been devised to assess severity and predict outcomes in patients with SAP. However, no single score has been proven to be superior to others and the search for an ideal scoring system continues[11]. Even though these tools are commonly used in clinical practice, they have low accuracy (60%-80%)[12]. Further, these models are complex, difficult to compute and have low specificity and positive predictive value. Moreover, some of these scoring systems, like Glasgow and Ranson scores, take 48 h to complete and are not devised for serial measurements[13].

AI tools like ANN have been utilised to develop algorithms based on routine blood and serum biochemical parameters to reliably predict severity of AP[14]. When compared to different clinical scores, ANN based models have performed better than Ranson’s, APACHE II, and modified Glasgow score in predicting severity in patients with AP[15-17]. Additionally, ANN based tools require lesser parameters and may be computed within 6 h of presentation, as opposed to some scores which may require up to 48 h.

Prediction of complications and organ failure

Majority of deaths due to AP, especially those occurring in the first week, are secondary to progressive organ failure[18, 19]. Moreover, progressive organ failure is the primary determinant of SAP, irrespective of any local pancreatic complication. Hence, it is imperative to determine patients at risk of developing organ failure and ensure an early

Table 1 Potential clinical applications of artificial intelligence in critical care gastroenterology

Organ involved	Clinical condition	Clinical applications
Pancreas	Acute pancreatitis	Prediction of severity; Prediction of local and systemic complications; Prediction of organ failure; Prediction of mortality
Liver	Chronic liver disease	Diagnosis; Staging of fibrosis; Prediction of complications; Predicting disease progression; Prognosis; Predicting need for liver transplantation
	Liver lesions/tumours	Diagnosis and classification; Differentiating between benign and malignant lesions
	Hepatocellular carcinoma	Diagnosis; Staging; Response to therapy
Intestine	Gastroesophageal reflux disease	Diagnosis
	Helicobacter pylori infection	Diagnosis
	Intestinal lesions	Diagnosis; Differentiating between benign and malignant lesions
	Intestinal bleeding	Predicting risk of bleeding and re-bleeding; Diagnosis; Identifying source of bleeding
Gall bladder and bile duct	Gall stones	Diagnosis; Removal of stones; Predicting need and difficulty of ERCP
	Bile duct obstruction	Diagnosis
Gastro-surgery	Appendicitis	Diagnosis
	Liver transplantation	Predict post-operative course; Predict graft failure; Predict recurrence of HCC; Predict in-hospital mortality
	Abdominal aortic aneurysm	Diagnosis; Prediction of post-operative complications; Prediction of post-operative mortality

ERCP: Endoscopic retrograde cholangiopancreatography; HCC: Hepatocellular carcinoma.

diagnosis of any organ dysfunction. ANN based model utilising commonly employed patient and laboratory parameters have been shown to accurately predict development of organ failure in AP patients[20].

AI based tools like regression tree algorithms and ANN have been used to predict complications such as acute lung injury, ARDS, portal vein thrombosis and porto-spleno-mesenteric vein thrombosis in patients with AP and AI has been proven to be more accurate than logistic regression based models in predicting these complications[21-25].

Prognostication

In spite of recent advances, mortality associated with SAP remains significant[26]. The overall mortality of ANP is approximately 15%–20%, of which there is a further twofold increase in a third of ANP cases where the necrotic tissue becomes infected[27,28]. Better understanding of risk factors associated with poorer clinical outcomes may help the physicians in instituting therapeutic measures and prognostication, as early intervention, within first 48 h, may help in improving outcomes[29].

Even though several clinical scores are commonly employed to aid in prognostication, these scores have several limitations. AI algorithms based on ANN have been shown to be better than these clinical scores in predicting clinical outcomes including length of hospital stay in patients with acute pancreatitis. Keogan *et al*[30] used ANN based on radiological and laboratory data from pancreatitis patients which performed better than both the Balthazar and Ranson scoring systems.

Data collected from acute pancreatitis patients from the Medical Information Mart for Intensive Care-III (MIMIC-III) database has shown that AI based algorithm can be effectively used to predict in-hospital mortality with an area under the curve (AUC) of 0.769. Further, AI based algorithms performed better than the commonly used scoring systems including SOFA score (AUC 0.401) and Ranson score (AUC 0.652) and logistic regression analysis (AUC 0.607) in predicting in-hospital mortality[14,31,32].

LIVER DISORDERS

Acute liver failure is a common indication for ICU admission. Patients with chronic liver disease (CLD) may also require ICU support in case of acute decompensation, development of acute on chronic liver disease or due to natural progression of CLD. Even ICU patients may develop liver dysfunction necessitating early diagnosis and intervention for improving prognosis. AI may have a potential role in early diagnosis of acute decompensation, identification of complications and prognostication in patients with liver disease.

Diagnosis of CLD

In critically ill patients, bedside ultrasonography is primarily used for diagnosis of CLD. However, it is operator dependant, qualitative in nature and have limited accuracy. Further, it may be difficult to distinguish fatty changes from early cirrhosis because of overlapping features[33]. Machine learning algorithms based on ultrasound have been applied for analysis of steatosis and the staging of liver fibrosis. Using ultrasound images, CNN based AI model has been shown to effectively assess the amount of liver steatosis with an area under the receiver operating curve (AUROC) of 0.98[34]. Deep learning-based algorithms have shown to improve accuracy for diagnosis of CLD with an AUROC of 1.0 as compared to conventional AI algorithms developed using SVM[35]. Furthermore, ML algorithms based on simple patient (age) and laboratory parameters (aspartate aminotransferase, albumin, and platelet count) have also been shown to accurately predict advanced fibrosis[36].

Liver fibrosis strongly correlates with development of hepatocellular cancer (HCC) and poor outcomes in patients with CLD. Liver biopsy remains the gold standard for detection and quantification of fibrosis. As it is an invasive procedure, it is associated with several inherent complications, especially in more vulnerable critically ill patients. Hence, non-invasive tests like bedside transient elastography measuring liver stiffness are being evaluated for such clinical conditions helping in bedside diagnosis and staging of liver fibrosis. Even though it is a comparatively newer test, it may find better applicability in ICU patients because of its high accuracy, easy repeatability, and non-invasive nature[37]. It has been shown that, AI based on transient elastography scans may further improve its accuracy and reduce subjectivity and inter-observer variations[38,39].

As AI based tools including ANN have been shown to reliably predict significant fibrosis in patients with chronic hepatitis, AI may be helpful in accurately staging liver fibrosis and may help in reducing the need for invasive procedures like liver biopsy[40,41].

Prediction of complications

CLD patients are at risk of developing local and systemic complications which may sometimes be life-threatening. Among the local complications, variceal bleed remains a common cause for increased morbidity and mortality in CLD patients. Hence, prediction and prevention of variceal bleed may improve clinical outcomes. Certain clinical scores (Child-Pugh score) and clinical parameters (hepatic-venous pressure gradient) have been successfully used as prognostic factors to stratifying the risk of variceal rebleeding[42]. However, they have limited accuracy. Diagnosis of varices requires endoscopy, which may not be feasible in many critically ill patients due to its invasive nature. ANN and ML based tools have been used to accurately predict presence of esophageal varices, obliviating the need for invasive endoscopy[43,44]. AI based algorithms also have the potential to accurately predict the risk of rebleeding in patients with liver cirrhosis which may aid the clinicians in managing such patients[45].

Prognosis

Short term prognosis of CLD depends upon development of complications and other organ dysfunction. ICU patients with CLD have high mortality rates especially if they develop other organ dysfunction requiring renal replacement therapy or invasive mechanical ventilation support[46]. On the other hand, long term prognosis depends on disease progression. Studies have shown that AI may be instrumental in identifying the cirrhotic patients at risk for disease progression and development of liver related complications including HCC, death, hepatic decompensation and even need for liver transplantation[47,48]. In CLD patients, DL-based model has been shown to be a good predictor of transplant-free survival at 1 and 3 years after diagnosis[48]. ANN algorithms based on clinical and laboratory parameters have been shown to accurately predict 1 year mortality in patients with CLD. This may aid in patient selection for liver transplantation[49].

Development of HCC may also impact clinical outcomes in such patients. ML has been employed for predicting development of HCC, diagnosis of HCC and even prediction of response to therapy[50-52].

AI may also be helpful in diagnosing focal liver lesions. AI based tools have shown to be useful in diagnosing and classifying liver nodules (cysts, hemangiomas, HCC) using ultrasound images[53,54]. DL and CNN based algorithms using MRI images, have also been shown to be effective in differentiating benign and malignant liver tumors, and classifying HCC and other tumors[55,56].

Response to therapy

In patients with liver disease it may be useful to identify patients who may respond to therapeutic interventions. This may aid in patient prognostication and triaging of limited ICU resources. ANN based models have been used to accurately predict the response to therapy with pegylated interferon alpha and ribavirin in patients with chronic hepatitis C infection, with sensitivity and specificity approaching 90%[57]. AI may also aid in predicting outcomes and risk for complications in post-liver transplantation patients[58].

INTESTINAL DISORDERS

Endoscopy is frequently employed to evaluate the gastro-intestinal tract. As it is an invasive procedure, it may be difficult to perform and associated with significant complication rates especially in critically ill ICU patients[59].

Diagnosis

Diagnosis of common GI disorders can be aided with AI based technology. ANN based model has been shown to reliably diagnose gastroesophageal reflux disease non-invasively by employing only clinical parameters[60]. CNN model based on endoscopic images has been shown to accurately diagnose *Helicobacter pylori* infection. Further, it was shown that the time required by AI to analyze the endoscopy images and make a diagnosis was significantly less as compared to experienced endoscopists (3 min and 14 s *vs* 230.1 min)[61]. Even a recently published meta-analysis reported that CNN may be as accurate as experienced physicians in making the diagnosis of *Helicobacter pylori* infection[62].

AI based algorithms have been developed to diagnose and differentiate between malignant and non-malignant esophageal diseases like Barret's esophagus and squamous cell carcinoma[63]. Moreover, AI may even be helpful in identifying early neoplastic changes to ensure timely diagnosis which may enable early intervention and aid in improving outcomes[64].

Gastrointestinal bleed

GI bleed remains a common indication for ICU admission. Additionally, increased stress, use of steroids and presence of sepsis can predispose general ICU patients to develop GI bleed during their ICU course. Some bleeds, especially those involving the small bowel, may be difficult to identify and manage. Even though the causes for upper and lower GI bleed may be relatively easier to identify using endoscopic techniques, repeated endoscopies may be required in a significant proportion of patients at risk for recurrent bleed. This may be especially difficult in critically ill ICU patients, who may benefit most from such procedures. ML based algorithms using endoscopic images have been developed which may be useful in identifying the patients at risk of rebleed and increased mortality with up to 90% accuracy[65-68]. ML models based only on clinical parameters like age, presence of gastric ulcers or gastrointestinal disease, presence of underlying malignancy or infections and serum hemoglobin levels have also been developed which have shown to predict risk of rebleed up to 1 year with an accuracy of 84.3% which may obliviate the need for repeated bronchoscopies[69].

AI, using various algorithms, have been shown to be helpful in more accurately identifying the source of bleed in patients with small bowel bleed using images from capsule endoscopy, which may avoid further invasive tests[70-73].

Hence, AI have the potential to reduce the need for endoscopies, allow for quicker procedures (by shortening the time required for observation and analysis), and also decrease the necessity for performing endoscopic biopsies, which may be particularly beneficial for critically ill patients.

BILIARY DISORDERS

Endoscopic retrograde cholangiopancreatography (ERCP) is commonly employed to diagnose disorders of the gall bladder, bile duct and the pancreas. However, it may be difficult to perform and may be associated with significant complications. Hence, careful patient selection is of paramount importance. An ANN model has been shown to have better discriminant ability and accuracy than a multivariate logistic regression model in selecting patients for therapeutic ERCP[74]. Using data collected from endoscopic images, AI has also been used to predict difficult ERCP which may help in reducing the failure rates and performing safer procedures[75,76]. AI model based only on clinical markers has been shown be an important adjunct to more invasive procedures in evaluation of bile duct obstruction[77].

AI may also support the physicians performing the ERCP by helping to differentiate between benign and malignant lesions and aid in their classification[78,79]. AI based algorithms may also be useful in therapeutic ERCPs by increasing the probability of successful removal of biliary stones[75]. Further, data suggests that AI based interventions have the potential to reduce post-ERCP complications including acute pancreatitis[80].

Endoscopic ultrasound (EUS) has been introduced recently to aid in the diagnosis of pancreatobiliary diseases. However, the diagnostic accuracy of EUS also remains limited with most studies reporting the range to be 80%-95%[81]. AI may be instrumental in increasing the efficacy and accuracy of EUS in the diagnosis and prognostication of GI diseases [82].

GASTROINTESTINAL SURGERY

Patients frequently require ICU care in the peri-operative period of major GI surgeries for clinical stabilisation and optimisation of therapy. These patients require close monitoring for development of any post-operative complications which may affect their hospital course and increase morbidity or mortality. AI based tools may be instrumental in recognising patients at risk of developing post-operative complications who may benefit from intensive care and early intervention.

Acute appendicitis remains a common and dreaded abdominal emergency. However, its diagnosis is often missed, which may increase morbidity and mortality. ANN has shown promising results in diagnosis of acute appendicitis and has performed better than clinical scores like Alvarado clinical scoring system. This may aid in screening of patients presenting with acute abdomen and making an early diagnosis[83].

In patients undergoing liver transplantation, AI has been used to predict post-operative course, graft failure, recurrence of HCC and even survival after surgery[84-87]. ANN has also been used to predict in-hospital mortality in patients after primary liver cancer surgery[88].

Certain acute abdominal emergencies like abdominal aortic aneurysm (AAA) rupture may be associated with high mortality rates. Prompt recognition and early intervention may improve outcomes in such cases. CNN based model has been shown to have high accuracy of 99.1% with an AUROC of 0.99 for detecting AAA. Also, CNN based models may be effective in accurately detecting presence of any leak post AAA repair and predict in-hospital mortality in the post-operative period[89-91]. Further, AI using easily definable pre-operative parameters, has been shown to provide a simple and highly discriminant adjunct in accurately recognising patients at higher risk of death after AAA repair surgery[91].

Similarly, AI based algorithms have been used to predict clinical outcomes including post-operative complications and mortality in other major or emergency abdominal surgeries including bariatric and metabolic surgeries, duodenal switch surgeries, and even after inguinal hernia repair[92-95].

NON-CLINICAL APPLICATIONS

Apart from these clinical applications, AI may be helpful in several non-clinical applications in GI critical care. AI can help in assimilating and analysing huge databases, help in reducing human errors in data entry, and assist in conducting large scale multi-center trials[96]. These intelligent database systems can also improve adherence to current clinical guidelines and protocols and aid in performing clinical audits and improve performance. Further, AI may also be instrumental in providing a more individualised patient care, and hence pave the way for precision medicine in the field of gastroenterology[97].

LIMITATIONS TO AI APPLICATIONS

The literature regarding use of AI in healthcare settings is increasing. However, most of the present studies have small sample sizes and are retrospective in nature. The literature on ICU patients is even more limited, restricting the use of AI in these patients. Moreover, comparison between different studies is difficult, as they have used different types of AI tools, with new tools being added frequently. Use of patient data for developing AI algorithms may lead to privacy and medico-legal issues which need to be adequately addressed by designing and implementing appropriate regulations and guidelines. Further, issues related to liability, reliability and safety of AI applications need to be addressed before widespread implementation and acceptance of AI in the current healthcare system becomes possible.

FUTURE DIRECTIONS

AI may form an important component of healthcare management and a lucrative adjunct to intensive care physicians in the future. However, large scale trials need to be conducted, especially in ICU patients, to evaluate and validate the efficacy and safety of AI. Further, standardisation of AI tools and algorithms must be done to ensure their comparability. For AI to be integrated in the routine clinical practice, healthcare workers need to be trained regarding safe and effective use of AI to ensure its proper utilisation and interpretation. Appropriate rules and regulations must be implemented to prevent any violation of patient privacy and maintain confidentiality of patient data.

CONCLUSION

With a huge increase in digitalisation of data and increased availability of big data, AI holds immense promise to change the landscape of healthcare in the not-so-distant future. It has the potential to improve diagnostics, predict progression and complications, and predict outcomes of critically ill gastroenterology patients thereby, reducing medical errors, increasing efficiency and improving clinical outcomes. AI can potentially reduce the number of invasive procedures and hence, reduce complication rates and provide a safer environment. However, there still remains issues regarding its safety, liability, legality, and patient privacy, which need to be addressed before it is incorporated in mainstream clinical care. Even though it may not be able to replace the physician's clinical acumen, it can be a good supplement and may aid in improving patient care and safety.

FOOTNOTES

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